Shoshana Dobrow Riza

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The Dynamics of Developmental Networks

Shoshana Dobrow Riza
London School of Economics and Political Science
Department of Management
Houghton Street, London WC2A 2AE, UK
Email: s.riza@lse.ac.uk

Monica C. Higgins
Harvard Graduate School of Education
Gutman Building #425, 6 Appian Way
Cambridge, MA 02138
Email: monica_higgins@gse.harvard.edu

THE DYNAMICS OF DEVELOPMENTAL NETWORKS

ABSTRACT

This study explores the dynamics of developmental networks – the set of relationships a protégé names as taking an active interest in and action to advance his/her career. Although prior research has demonstrated the benefits of developmental networks, we know relatively little about how these networks change over time or the antecedents of developmental network dynamics. As research on career and adult development theory has suggested, professional development occurs within a dynamic, relational context; therefore, exploring network dynamics may enable future research to gain greater insight into how career trajectories unfold. In a 10-year, four-wave prospective longitudinal survey study of 136 U.S. business school students and their over 1600 relationships, we explore the dynamics of developmental networks, including the starting points (intercepts) and the rates of change (slopes) of the content of help provided (average career and psychosocial support) and the networks' structure (network density, tie closeness, and communication frequency). Our multilevel longitudinal analyses show how these network characteristics change over time and how the content and structure of the support provided covary. Further, we explore individual-level and organizational/industry-level antecedents of network change trajectories. We conclude with implications of our discoveries for future theory-building and research on developmental networks, mentoring, and careers, and offer suggestions for consideration for practice.

Keywords: Developmental networks, mentoring, careers, longitudinal

Mentoring scholars have long documented the professional benefits individuals receive from career-related developmental assistance (for reviews, see Allen & Eby, 2007; Allen, Eby, O'Brien, & Lentz, 2008; Haggard, Dougherty, Turban, & Wilbanks, 2011; Kammeyer-Mueller & Judge, 2008; Ragins & Kram, 2007). Whereas much of this research has focused on dyadic, hierarchical mentoring relationships, scholars have also broadened their perspective to consider the developmental support individuals receive from several potentially-interconnected people – that is, from their *developmental network* (Higgins & Kram, 2001). Developmental networks are comprised of "people a protégé names as taking an active interest in and action to advance the protégé's career by providing developmental assistance" (Higgins & Kram, 2001, p. 268). These networks generally consist of four to five "developers" who may know the protégé from a range of contexts, such as from inside or outside one's organization, and may be from any hierarchical level, namely peers or subordinates in addition to the more traditional superior role (de Janasz, Sullivan, & Whiting, 2003; Higgins & Kram, 2001; Higgins & Thomas, 2001).

Over the last two decades, research on developmental networks has grown and has generally focused on the benefits of two key categories of network characteristics: the *content* or type of support provided and the *structure* of the ties that comprise these networks (Cotton, Shen, & Livne-Tarandach, 2011; Dobrow, Chandler, Murphy, & Kram, 2012). Regarding network content, research shows that developers can provide different amounts of career and/or psychosocial help (e.g., Dreher & Ash, 1990; Kram, 1985), indicative of the "quality" of the developmental relationship (Higgins & Thomas, 2001). That is, developers may provide *career support*, which is help that involves sponsorship, exposure, and protection, and/or they may provide *psychosocial support*, which is help that includes friendship and caring beyond work and is of a relatively social and emotional nature (Kram, 1985). Regarding network structure, scholars often examine the diversity and strength of the ties comprising the network. One exemplar indicator of network diversity is *density*, which captures the degree to which developers know and/or are connected to one another and, thus, the extent to which information they provide may be redundant (Brass, 1995; Burt & Minor, 1983). Two indicators of tie strength are the degree of psychological *closeness* between protégés and developers and *communication frequency* (Marsden & Campbell, 1984). Developmental network content and structure have been associated with a variety of career outcomes, including work satisfaction, optimism, professional identity clarity, promotion and career advancement, and organizational retention (e.g., Dobrow & Higgins, 2005; Higgins, 2000; Higgins, Dobrow, & Roloff, 2010; Higgins & Thomas, 2001; Singh, Ragins, & Tharenou, 2009b).

Despite the considerable amount of research on how different developmental network characteristics impact individuals' career outcomes, we know very little about how these characteristics change over time. For example, it is unclear whether the content and/or structure of protégés' developmental networks increase, decrease, or remain stable over time. Although mentoring scholars acknowledge that developmental relationships are by their very nature dynamic and changing, we lack a substantial body of research that shows how these developmental network characteristics shift with time. These dynamics are important to understand, as adult and career development theorists have long suggested that professional development is embedded in important dynamic relationships (e.g., Hall, 2002; Ibarra, 1999; Levinson, Darrow, Klein, Levinson, & McKee, 1978; Schein, 1978; Super, 1992). Thus, delineating the change patterns of developmental network characteristics, and beginning to provide a methodology that highlights those dynamics, may help researchers gain greater insight into how career trajectories unfold.

Some studies have made efforts to examine the dynamics of developmental networks. For instance, one longitudinal study found that individuals who received more career and psychosocial support during early career, as well as increasing amounts of both types of support, experienced higher levels of optimism a few years later (Higgins et al., 2010). Another study found that over time, career support from one's entire developmental network was positively related to career-related self-efficacy and perceptions of career success, whereas career support from developers retained from graduate school was negatively related to perceptions of career success (Higgins, Dobrow, & Chandler, 2008). Cummings and Higgins (2006) examined networks over a short time frame and found evidence for an inner and outer core structure, providing preliminary evidence regarding the changing nature of developmental network structure. And, Dobrow and Higgins (2005) found that, on average, developmental network density increased over the span of two years and that an increase in density was associated with decreased clarity of professional identity several years later.

In adjacent research on social networks (Walter, Levin, & Murnighan, 2015), dyadic mentoring (e.g., Liu & Fu, 2011) and helping relationships (Golan & Bamberger, 2015), research has underscored the changing nature of individuals' relationships and networks. Yet, despite calls for longitudinal research, we lack research on the "career-spanning" nature of developmental networks (Cotton et al., 2011). And, while the above studies have yielded insights into the antecedents, consequences, and changing nature of some aspects of developmental networks, there is as-yet no comprehensive understanding of how the core network characteristics, network content and support, change or are interrelated over time.

Given this, our first research question is: *How do developmental network characteristics change over a substantial period of time?* In this study, we longitudinally tracked many network characteristics – specifically, network content (career and psychosocial support) and network structure (diversity as indicated by density and tie strength as indicated by closeness and communication frequency). Further, we explored if and how these five developmental network characteristics changed over a substantial timeframe of ten years, beginning when participants were completing an MBA program. We hope to offer the most comprehensive exploration of the dynamics of developmental network characteristics over a significant timeframe to date.

Our study also lends insight into how developmental network characteristics covary with one another. At present, we know very little about this aspect of network change because previous research on developmental networks has investigated developmental network characteristics independently of one another (e.g., Higgins et al., 2008). We thus have limited insight into if and how developmental network content and structure change relative to one another over time – or even whether individuals may experience tradeoffs among these. Thus, our second research question is, *How do the change trends of developmental network characteristics covary with one another?* We thus explored how the change trends of both developmental network content and structure covaried over time. Positive covariance between two change trends would indicate that individuals experienced changes in these two trends in tandem, whereas negative covariance would indicate a tradeoff from one developmental network characteristic to the other such that one goes up as the other goes down.

Addressing these questions is theoretically important because research on mentoring and developmental networks has long claimed that developmental relationships evolve in response to protégés' changing needs (e.g., Kram, 1983). Therefore, exploring patterns in these changes can provide a platform for theorizing more specifically about network dynamics. Our exploration may also lend insight into the theoretical claims of researchers who advocate for the importance of relationships in general (e.g., Berscheid, 1999; Ferris, Liden, Munyon, Summers, Basik, & Buckley, 2009), for a relational perspective on career and adult development (e.g., Ragins, 2011; Ragins & Verbos, 2007), and for research on leader development (e.g., McCall, Lombardo, & Morrison, 1988; Seibert, Sargent, Kraimer, & Kiazad, 2016).

Our longitudinal research design also allowed us to explore the *antecedents* of network change. The one extant review of developmental networks research called for research on two broad categories of network antecedents: protégé factors and contextual influences (Dobrow et al., 2012). And yet, these suggestions have remained largely unanswered for two primary reasons: First, most of the work in this area has been conceptual; there is simply very little quantitative research on developmental network dynamics or its predictors. Second, the emphasis in existing empirical research has been on career outcomes, as opposed to predictors. Thus, to address this call, we explored a third research question: *What factors predict the change trends of developmental network characteristics over time?*

In addition to addressing gaps in prior theory and empirical research, our study offers opportunities for methodological insights as well. In general, prior research has tended to employ cross-sectional or two-wave designs to examine developmental networks (see Dobrow et al., 2012 for a review) or the support provided by mentoring relationships (e.g., Wang, Tomlinson, & Noe, 2010), helping relationships (e.g., Li, Harris, Boswell, & Xie, 2011), and feedback relationships (e.g., Cianci, Klein, & Seijts, 2010). These approaches are potentially problematic for developing a deeper understanding of developmental network dynamics, as cross-sectional and longitudinal analyses can sometimes yield opposite results (Ployhart & Vandenberg, 2010). Thus, despite claims that relationships and networks are dynamic (Snijders, 2001, 2009), scholars have not yet employed sophisticated analytical techniques to fully investigate them. Our study thus offers an important contribution through utilizing methodological techniques that directly explore change over time, which scholars have become comfortable asserting and yet, often, uncomfortable investigating empirically. Specifically, building on the general recommendation that longitudinal designs include at least three waves of data (Ployhart & Vandenberg, 2010; Singer & Willett, 2003), we collected four waves of data that span 10 years. This approach enabled us to examine both the starting points (intercepts) and the rates of change (slopes) of the five developmental network characteristics, as well as how these intercepts and slopes covary and predictors of these change trajectories.

In sum, this study makes several contributions, particularly to the developmental networks literature. First, it offers the first comprehensive investigation of the change patterns of both the content and structure of people's developmental networks – five characteristics in total – over the course of a decade, and so reveals the dynamic patterns through which people receive developmental support in their careers. Second, we examine the covariation among different developmental network characteristics' change trends, which contributes to our understanding of the interplay between various indicators of network "quality" studied in the past. Third, building on the largely conceptual research about the antecedents of developmental networks (for exceptions, see Burke, Bristor, & Rothstein, 1996; Cotton & Shen, 2013), the present study quantitatively explores how possible antecedents, both at the individual and organizational/industry levels, relate to developmental network dynamics. We thus shed light on how changes in developmental network characteristics are, and are not, shaped over time, thereby offering theoretical and empirical discoveries for future research and practice.

METHOD

Sample and Procedure

This longitudinal survey study includes four waves of data spanning ten years (1996-2006). Participants were students in a top-twenty United States East Coast full-time MBA program at the time of the first data collection (“Time 1”), which occurred soon before their graduation.[1] In this initial sample for the study, the participants were 72% male, 75% Caucasian, had 3.7 years of previous work experience, and were an average of 27.8 years old. For the first follow-up survey (“Time 2”), which occurred approximately two years later in 1998, we invited all 136 participants from the Time 1 sample to participate (response rate = 79%, n = 108). The third survey (“Time 3”) took place three and half years later, or five and a half years after graduation. We invited all participants from the Time 1 sample to participate regardless of whether they had completed the Time 2 survey (response rate = 64%, n = 87). For the fourth data collection (“Time 4”), which occurred four and half years later, or ten years after graduation, we again contacted all participants from the Time 1 sample to participate, regardless of whether they had completed the Time 2 or Time 3 surveys (response rate = 57%, n = 77). In total, participants completed 408 total surveys across the four waves of the study and reported on over 1600 relationships. The surveys focused on measuring developmental network characteristics and also included items regarding participants’ careers and lives.

This study’s longitudinal timeframe spanned the period in participants’ lives when they were launching their post-graduate careers, namely choosing their initial jobs post-MBA and career-building over the next decade. This design thus captures participants’ start from comparable baselines and, further, allows for the exploration of developmental networks’ initial levels and evolution during a time when they should be directly relevant to participants’

[1] Sixty-seven of the initial 136 participants were invited to participate in the study during a group meeting, during which they completed the 1.5 hour survey (out of 87 present, 77% response rate). A random sample of 300 additional students was contacted to participate, and 69 completed the survey via mail (23% response rate). There were no statistically significant differences between the two subsets of the initial sample with respect to any of the study’s core variables.

vocational choices and subsequent careers. Table 1 provides an overview of measures collected at each time period.

Insert Table 1 about here

Measures

Developmental network characteristics. Participants responded to a name generator question about their *current* developmental network on each survey: "Please consider the people who you believe currently – i.e., some time over the last year – take an active interest in and concerted action to advance your career…they may be people with whom you work or have worked, friends, or family members….and they may assist you with personal as well as professional development." This question is consistent with social network research on "current" relationships that refer to a one-year time frame (e.g., Burt, 1983). This question tended to elicit about four developers, consistent with content-based network research (Podolny & Baron, 1997) and yielded data on over 1600 relationships across the four waves of data collection.

Participants responded to this question independently at each time point; the surveys did not prompt participants with the names provided on previous surveys. Participants then answered several questions about each named developer. Based on these responses, we calculated five measures – two about developmental network content and three about structure – each of which measures characteristics of the developmental network as a whole. We measured all developmental network characteristics during all four data collections, resulting in network content and structure measures for participants at each point in time.

Developmental network content. Participants indicated the extent to which they received two types of developmental support, *career* and *psychosocial* help (Kram, 1985). Participants completed a 5-item scale about the career support they received from each developer at each point in time (e.g., "creates opportunities for visibility for you" and "opens doors for you professionally") and a separate 5-item scale about the psychosocial support they received from each developer (e.g., "cares and shares in ways that extend beyond the requirements of work" and "is a friend of yours"). All items used a 7-point scale (1 = *never; not at all*, 7 = *to the maximum extent possible*). These scales are consistent with prior research on mentoring and developmental networks (e.g., Higgins et al., 2010; Higgins & Thomas, 2001).

For each participant-developer relationship within the developmental network, we calculated the average of the five career support items and, separately, the five psychosocial items. We then calculated the average amount of support provided by all individual alters in the developmental network as the average amount of career support reported across all participant-developer relationships within each protégé's network ("average career support") and the average amount of psychosocial support reported across all participant-developer relationships within each protégé's network ("average psychosocial support"). Consistent with prior developmental networks research (e.g., Higgins & Thomas, 2001), this method provides a measure of the *average amount of support* provided by the developmental network as a whole, accounting for the number of relationships that comprise it. It is not simply a sum, which would yield biased parameter estimates for the two types of support and would be largely determined by network size.[2] Prior research suggests that these measures of average career and psychosocial support are indicators of the "quality" of the developmental network as they provide an overall assessment of the help that flows across the network's ties (e.g., Higgins & Thomas, 2001).

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[2] The limitation of this "sum" approach is that the total amount of support is strongly determined by the size of the network. Nonetheless, we ran alternative versions of our full models, including network size as a predictor, using the sum calculation as the dependent variable. The results were similar to using average career and psychosocial support, with two exceptions. The results for career support changed slightly such that although there was a positive relationship between the time variable and the amount of career support provided when we looked at career support as an average, it was not significant when looking at is as a sum. And, for psychosocial support, we found that network size was a significant and positive predictor, such that larger networks provided more total psychosocial support, in contrast to our core model, in which network size was a significant and negative predictor.

Developmental network structure: Diversity. We examined one exemplar of the degree of diversity of a developmental network's structure, *density*. According to social networks research, network density, which captures the extent to which developers in the network know and/or are connected to one another, reflects the degree to which the information within a network is more or less redundant (Brass, 1995; Burt & Minor, 1983). Lower density indicates less redundancy, which suggests greater access to diverse information (Higgins, 2001b; Higgins & Kram, 2001). Here, for each possible pair of developers in the developmental network, participants indicated whether the members of the pair knew one another. Consistent with prior research, we calculated density as the number of these "knowing ties" divided by the number of possible ties in the entire developmental network (Anderson, Butts, & Carley, 1999).

Developmental network structure: Tie strength. We measured two types of tie strength. First, we assessed the degree of psychological *closeness* between the protégé and his/her developers (Marsden & Campbell, 1984), such that closer ties reflect stronger ties. We asked participants, "How close are you to each person?" The instructions indicated that very close relationships are characterized by high degrees of liking, trust, and mutual commitment and distant relationships are characterized by not knowing the person very well or by having very little liking, trust, and mutual commitment. Participants responded for each developer in their network using a 4-point scale, where 4 = *Very close*, 3 = *Close*, 2 = *Less than close*, and 1 = *Distant*. As with network content, we averaged the closeness ratings reported across all protégé-developer relationships within each protégé's network, rather than calculating a sum, to represent closeness for the overall network and to enable an investigation of how closeness covaries (or not) with other developmental network characteristics, accounting for network size.

Second, we assessed *communication frequency*, another measure of tie strength, which captures how often protégés and their developers communicate (Marsden & Campbell, 1984). More frequent communication reflects a stronger tie. We asked participants, "How often do you communicate with each person?" At Time 1, participants used a 4-point scale ranging from 1 = *Daily* to 4 = *Less than monthly*. At Time 2, participants used a 7-point scale ranging from 1= *More than once daily* to 7 = *Less than once monthly*. At Times 3 and 4, participants used a 7-point scale ranging from 1 = *Less than once monthly* to 7 = *More than once daily*.

To prepare these measures for use in analyses, we first reverse coded Times 1 and 2 to match the direction of Times 3 and 4, such that lower values indicate less frequent communication and higher values indicate more frequent communication. Next, to adjust for the different scales used in Time 1 compared to Times 2 through 4, we transformed all items' values using the POMS (proportion of maximum scaling) transformation. POMS transforms our items' original 1-to-4 and 1-to-7 scales into a 0-to-1 scale.[3] The benefit of this transformation, in contrast to standardization, is that it maintains the proportions of the differences between values from the original scales, which thus allows us to examine our research questions about change in this network characteristic over time. Standardization creates numerous challenges for longitudinal studies, including that the items' means become zero, which would preclude examining whether these means change over time (Moeller, 2015). We calculated communication frequency for the overall developmental network by taking the average of the ratings reported across all participant-developer relationships within each protégé's network,

[3] The POMS transformation transforms each scale to a metric from 0 (= minimal possible) to 1 (= maximum possible) by first making the scale range from 0 to the highest value, and then dividing the scores by the highest value: POMS=[(observed−minimum)/(maximum−minimum)]. For instance, for our 1 to 4 scale, first we calculated each observed value minus 1 (which shifts the scale to 0 to 3), and then divided that score by 4-1 (i.e., 3) to yield the 0 to 1 scale Moeller, J. 2015. A word on standardization in longitudinal studies: don't. ***Frontiers in Psychology***, 6: 1389; doi:10.3389/fpsyg.2015.01389..

such that lower values indicate lower frequency and higher values indicate higher frequency. Again, we opted not to calculate a sum, as this would be largely determined by network size.

Developmental network size. We created a time-varying measure of *developmental network size* based on the number of developer names participants provided at each time point. Consistent with prior developmental network research (e.g., Cummings & Higgins, 2006), we included this measure to ensure that our analyses captured the effects of network size on each of the developmental network characteristics just described.

Predictors of developmental network characteristics. We explored an array of *individual-level variables* as possible predictors of developmental networks' change trajectories: gender (1 = *female*, 0 = *male*); ethnicity (1 = *Caucasian*, 0 = *non-Caucasian*); time-varying marital status (1 = *married*, 0 = *unmarried*; measured at each data collection), citizenship (0 = *U.S.*, 1 = *Non-U.S.*), and years of work experience prior to starting their MBA. We also explored several *organizational/industry-level variables* that could relate to individuals' developmental network characteristics. We focused on the industry in which participants worked prior to entering their MBA program by including dummy variables for the three dominant industries in this sample: Financial Services, Consulting, and Technology, each coded as 1 = *Worked in this industry*, 0 = *Did not work in this industry*).

Analytic Strategies

Change trends of developmental network characteristics. We conducted analyses in three steps to match our three research questions. First, we used multilevel modeling to model the change trend of each developmental network characteristic and selected the best fitting model. In this 2-level model, the lower level ("Level 1") is the wave of data collection, allowing exploration of what occurs *within individuals*, and the upper level ("Level 2") is the individual, allowing exploration of what occurs *between individuals* (Singer & Willett, 2003).[4]

More specifically, we fit a set of multilevel models to our data, which meet the requirements for applying multilevel modeling (Singer & Willett, 2003), using full maximum likelihood estimation in SPSS's mixed procedure (see Appendix for definitions and formulae of the models). The parameter estimates and corresponding *p*-values of the predictor variables reflect the direction, size, and significance of their relationships to the developmental network characteristics, just as in multiple regression models. The time variable, "YEARS," captures the passage of time over the course of the study. The intercept represents the initial level of the developmental network characteristic – that is, when YEARS is 0, as participants were just about to graduate from their MBA program (Time 1). YEARS at Time 2 is 2 (i.e., 2 years later), YEARS at Time 3 is 5.5 (i.e., 5 ½ years after Time 1), and YEARS at Time 4 is 10 (i.e., 10 years after Time 1). As the longitudinal dataset spans 10 years, the model thus estimates growth trajectories spanning the first decade of our participants' post-MBA careers.

For each of the five developmental network characteristics, we estimated four models of increasing polynomial complexity to examine change trends (see Appendix). All models included time-varying developmental network size as a predictor to account for inter-individual differences in the intercept based on network size. The first model ("Model 1a: No change") did not include a time predictor, and so estimates the grand mean level of the developmental network

[4] At Level 1, we examined the relationship between time and the developmental network characteristics. This generates the Level 1 parameters, an intercept and slope(s), which determine the shape of each individual's "true trajectory of change" Lenzenweger, M. F., Johnson, M. D., & Willett, J. B. 2004. Individual growth curve analysis illuminates stability and change in personality disorder features. ***Archives of General Psychiatry***, 61: 1015-1024. because the intercept parameter represents an individual's true value of a given developmental network characteristic at the beginning of the study and the slope parameter(s) represents an individual's true rate of change in the developmental network characteristic over time. The Level 2 model tests how the intercept and slope(s) from Level 1 relate to between-subjects factors (e.g., network size or the individual- and organizational/industry-level characteristics for Research Question 3).

characteristic over time. The second model ("Model 1b: Linear change") includes time (the variable "YEARS") as a predictor. The third model ("Model 1c: Quadratic change") investigates whether the developmental network characteristics followed a curvilinear, rather than linear, trajectory over time. To do so, we expanded Model 1c by adding a quadratic time predictor (i.e., $YEARS^2$). The fourth model ("Model 1d: Cubic change") investigates whether the developmental network characteristics followed a cubic, rather than linear or quadratic, trajectory over time. We extended Model 1c by adding a cubic time predictor (i.e., $YEARS^3$).

To establish the best-fitting change model for each developmental network characteristic, we compared each model to the previous model (i.e., 1b to 1a, 1c to 1b, etc.) to determine if the addition of a subsequent time predictor improved the model fit or not (Barnett, Marshall, & Singer, 1992; Singer & Willett, 2003). We calculated the difference in the deviance statistics (- 2 log likelihood) between the first two models, 1b compared to 1a, and tested whether this amount exceeded the critical value of a chi-square distribution (where the degrees of freedom equals the number of parameters by which the two models differ). If the amount did not exceed the critical value, we concluded that Model 1a fit better than 1b. If the amount exceeded the critical value, we concluded that Model 1b better fit the data than Model 1a and proceeded to compare Model 1c to Model 1b, and so forth. We retained the best fitting model for each developmental network characteristic as our baseline upon which to build our subsequent analyses. This approach allowed us to firstly describe the change trend for each developmental network characteristic (i.e., no change, linear change, quadratic change or cubic change) and, then, test for predictors of this change trajectory in the third step of our analyses (below).

***Covariation of change trends among developmental network characteristics*.** In the second step, which addresses our second research question, we estimated the correlations among the intercepts and slopes of the five developmental network characteristics (Song, Liu, Shi, & Wang, 2017). We generated these values for each developmental network characteristic from the best-fitting model from the first step of our analyses.

Predictors of developmental network characteristics. In the third and final step, for our third research question, we fit the full multilevel model ("Model 2: Full") for each developmental network characteristic. This model examined all 5 individual-level and all 3 organizational/industry-level variables as predictors (see Appendix). To compare the multilevel models (Models 1a, 1b, 1c, 1d and 2) for a given developmental network characteristic to one another, they must include identical observations (i.e., identical data, where the data consist of "observations," or instances of measuring a variable from a participant at a particular time). In all stages of our analyses, we thus analyzed participants whose data were complete across all models for a given developmental network characteristic in order to utilize the maximum number of observations possible: 378-386 observations from 129-131 people, an average of close to 3 observations per person.

RESULTS

Table 2 shows means, standard deviations, and correlations for all measures. Tables 3a-3e present the coefficient estimates for each developmental network characteristic's multilevel models. Table 4 shows the correlations among intercepts and slopes. Figure 1 provides a graphical representation of the full model results for each developmental network characteristic.

<u>Insert Table 2 about here</u>

Change Trends of Developmental Network Characteristics

Developmental network content. For average career support, the quadratic change model (1c) fit the data best. An examination of the parameter estimates in Table 3a (Models 1a-1d) and the plotted curve in Figure 1 shows that the amount of average career support participants received from their networks as a whole increased over time, but the increase slowed down starting in years 5 and 6 and larger sized networks even began to decrease. Further, the variance of the intercept was significantly different from zero (variance = .65, $p < .01$), indicating that there were inter-individual differences in the initial level of average career support. That is, participants differed from one another in terms of how much average career support they received as they were graduating from their MBA program. However, the variances for linear and quadratic slope were not significantly different than zero. Therefore, there was heterogeneity in the initial level, but not slope, for antecedents (i.e., level-2 predictors) to try to explain.

For average psychosocial support, the linear change model (Table 3b, Model 1b) was the best fitting model. The time variable (YEARS) was not significant, thus indicating that the whole sample did not experience change over time on average. However, Figure 1 shows that average psychosocial support did, in fact, increase over time (e.g., from 5.56 at Year 0 to 5.71 at Year 10 for an average sized network). This increase results from the effect of the time-varying predictor, developmental network size, on average psychosocial support. Specifically, the *increase* in average psychosocial support over time results from developmental network size, which is negatively related to average psychosocial support, declining over time – that is, as network size decreases, average psychosocial support increases. Similar to our discoveries for the dynamics of average career support, the variance of the intercept was significantly different from zero (variance = .57, $p < .001$), indicating that participants differed from one another in how much average psychosocial support they received as they were graduating from their MBA program, but the variance for slope was not significantly different from zero.

Developmental network structure. For density, the quadratic change model (Table 3c, Model 1c) fit the data best. Figure 1 highlights that density initially increased for about 3 to 4 years, then declined for the remainder of the study. As with our findings for both content characteristics, there was significant heterogeneity in density's initial level (variance = .03, $p < .05$), but not its linear or quadratic slopes.

For closeness, the no-change model (Table 3d, Model 1a) fit the data best. Yet, Figure 1 shows an increase in closeness over time (from 3.41 at Year 0 to 3.55 at Year 10 for an average sized network). As with the results for average psychosocial support, the negative relationship between time-varying developmental network size, which decreased over time, and closeness resulted in an increase in closeness over time. The variance of the intercept was significantly different from zero (variance = .05, $p < .001$), indicating that participants differed from one another in their initial levels of closeness. Lastly, although the time predictor (YEARS) was not in the best fitting model (Model 1a), we opted to include this predictor in our subsequent model testing to align with the exploratory approach of the present study, to allow for its interaction with time-varying network size (see below), and to be consistent with the other developmental network characteristics' models.

For communication frequency, the linear change model fit the data best (Table 3a, Model 1b). Figure 1 highlights that communication frequency increased over time (from .56 at Year 0 to .67 at Year 10 for an average sized network). There was heterogeneity in the initial level (variance = .01, $p < .001$), but not slope, of communication frequency, consistent with our findings for the other network characteristics.

Covariation of Change Trends among Developmental Network Characteristics

We explored the covariation of the intercepts and slopes of the five developmental network characteristics by correlating the predicted values generated by the best fitting growth models for each individual in the sample. The exception to this was closeness, for which we generated the predicted values from Model 1b, rather than from its best-fitting model (the no-change model, 1a), so that we could include a predicted value not only for intercept but also for slope. This is also consistent with our choice to retain the time predictor for use in the full model for closeness (see Table 3d, Model 2).

As shown in Table 4, several intercepts were positively correlated with one another: average career support and average psychosocial support (r = .29, p < .01), average psychosocial support and closeness (r = .65 p < .01), average psychological support and communication frequency (r = .40, p < .01), density and closeness (r = .30, p < .01), density and communication frequency (r = .28, p < .01), and closeness and communication frequency (r = .57, p < .01). Thus, participants who started with a higher (lower) level of average career support were also likely to start with a higher (lower) level of average psychosocial support, and those who started with a higher (lower) level of average psychosocial support were also likely to start with a higher (lower) level of closeness and so on.

There were two significant correlations between slopes: a positive relationship between the slopes of average career support and density (r = .28, p < .01) and between the slopes of closeness and communication frequency (r = .36, p < .01). These findings suggest that when average career support increased at a higher rate, density also increased at a higher rate (and vice versa), and when communication frequency increased at a higher rate, closeness also increased at a higher rate (and vice versa).

Predictors of Developmental Network Characteristics

The full models included all five individual- and all three organizational/industry-level variables as predictors of each developmental network characteristic's intercept (see Tables 3a-3e, Model 2), the linear and/or quadratic time variable(s), and developmental network size. We also included the interaction of developmental network size and time to allow the effect of this time-varying predictor on the outcome to vary over time (Singer & Willett, 2003). We did not include between-individual predictors of slopes in the full models as none of the best fitting models yielded significant between-individuals variance.

Figure 1 provides a graphical interpretation of the full model results and the effects of the key significant predictor across models, time-varying developmental network size. It displays predicted values across time for each of the five developmental network characteristics for three prototypical participants: (1) a participant with *high* developmental network size over time (i.e., one standard deviation above the mean), (2) a participant with *low* developmental network size over time (i.e., one standard deviation below the mean), (3) and a participant with *average* developmental network size over time. We held the remaining variables in the model constant at their means, including using time-specific means for time-varying variables.

Developmental network content. For average career support, developmental network size was a significant and positive predictor of the intercept ($\beta = .21$, $p < .05$). As shown in Figure 1, participants with larger networks started off with the highest average amount of support received from their developmental networks, and those with smaller networks started out with the lowest average amount of support received. All three prototypical participants experienced an increase in average support over time. This shifted about 5 to 6 years out after earning their MBAs, such that participants with smaller networks received the most average career support from then until the end of the study timeframe. Given that scholars typically view career support as beneficial to individuals' careers (Dobrow et al., 2012), our results suggest that considering its dynamics over time is critical: looking at participants only at the beginning of the study indicates that those with larger networks received the most average career support, consistent with prior research (Higgins, 2000, 2001b); however, looking at participants over time shows that by 10 years later, those with smaller networks received the most average career support.

For average psychosocial support, developmental network size was associated with a lower intercept ($\beta = -.11$, $p < .05$), such that participants with larger networks received lower amounts of average psychosocial support at the start of their post-MBA careers. Being a non-US citizen was associated with a lower intercept ($\beta = -.41$, $p < .01$). In Figure 1, all three prototypical participants experienced an increase over time. We note the unexpected finding that smaller networks provided *more* average support over time than larger networks. On average, each developer in a smaller network generally provided more support than each developer in a larger network, thus yielding higher average psychosocial support from the network.

Developmental network structure: Diversity. For density, developmental network size was a significant and positive predictor of the intercept, such that larger networks started off being more dense ($\beta = .04$, $p < .05$). Marital status was associated with a higher intercept ($\beta = .08$, $p < .05$). The three prototypical participants in Figure 1 experienced similar curves to one another in that their density initially increased for a few years, then decreased for the remainder of the study. Larger networks were the most dense over time, such that developers in these networks knew one another to a greater degree than in smaller networks. Indeed, smaller networks became less dense over time to the point that the predicted level of density after 10 years was around zero, meaning that none of the developers would know one another.

Developmental network structure: Tie strength. For closeness, developmental network size predicted a lower intercept (β = -.13, $p < .001$), such that participants with larger networks experienced less average closeness at the start. Further, being a non-US citizen was associated with a lower intercept (β = -.18, $p < .01$). All three prototypical participants in Figure 1 increased over time. Smaller networks started off being the closest and larger networks were the least close. The gap between smaller and larger networks narrowed over time due to larger networks increasing in closeness more rapidly and, so, approaching smaller networks' level.

For communication frequency, developmental network size predicted a lower intercept (β = -.04, $p < .001$), such that participants with larger networks experienced less frequent communication at the start. Additionally, married participants (β = .05, $p < .05$), US citizens (β = -.07, $p < .01$), and those who had previously worked in consulting (β = .06, $p < .05$) started with more frequent communication. All three prototypical participants' networks increased over time (see Figure 1). Smaller networks started off with the most frequent communication and larger networks started off with the least frequent communication. These relative positions remained intact over time. As with our other measure of tie strength, closeness, smaller networks were stronger in terms of higher communication frequency than larger networks. These results across all five developmental network characteristics indicate that considering dynamics of these developmental network characteristics provides insights above and beyond a snapshot view.

<u>Insert Tables 3 and 4 and Figure 1 about here</u>

Supplementary Analyses

As supplementary analyses, we estimated an alternative version of the full models in which we included an additional characteristic of participants' organizational context as a predictor of intercept: the cumulative number of employers participants had had over the 10-year study (*M* = 3.45, *SD* = 1.14). This variable could be an important predictor of developmental network characteristics. For instance, spending one's career in more organizations could lead to more connections to more varied people, thus resulting in lower density. Or, moving across multiple organizations could lead to a greater need for career and/or psychosocial support to effectively manage these transitions. However, the models produced a pattern of results similar to the core analyses: developmental network size continued to be the primary predictor; number of employers was not a significant predictor of intercept for any of the five developmental network characteristics.[5]

As a second set of supplementary analyses, we conducted a post-hoc analysis of developmental network size. In our core analyses, developmental network size was the key predictor of initial levels of all developmental network characteristics. Given this, we explored what predicts developmental network size. We ran Models 1a, 1b, 1c, 1d and 2 with developmental network size as the dependent variable and the other predictors the same as in our core analyses. First, in examining the change trends for developmental network size, the best fit was the linear change model (Model 1b), in which there was an average decline in developmental network size over time ($\beta = -.08$, $p < .001$). The significant between-individual variances for both intercept (variance = .75, $p < .001$) and slope (variance = .01, $p < .05$) indicate that there were, indeed, level-2 differences to predict. However, in the full model (Model 2), we found no significant predictors of intercept or slope, and this model did not fit the data significantly better than Model 1b. Thus, in our sample, we found no predictors of

[5] Whereas our full models in Tables 3a-3e ran on 378-386 observations (time points of data) from 129-131 people, including the number of employers variable reduced the sample by approximately half, to 202-206 observations from 62 people. This is due to missing data for the number of employers variable, which required responses from each participant across all waves of data collection to be calculated. Nonetheless, the consistent pattern of results between these supplementary analyses and our core analyses highlights the robustness of our core findings.

developmental network size other than the decline that occurs with time.

Goodness-of-Fit and Sensitivity Analyses

Across the full models, the level-2 variance component for the intercepts was significantly different from zero (*p*s < .05) for four of the developmental network characteristics and marginally significant ($p = .06$) for the fifth, density. Thus, there was variability in initial levels of these developmental network characteristics remaining to be explained by factors *beyond* the predictors in the model.

Tables 3a-3e summarize model fit statistics. A comparison of the deviance statistics (-2 Log-Likelihood) revealed significant ($p < .05$) differences in the fit of the full model relative to the best-fitting change trend models for density, closeness, and communication frequency and marginally significant ($p = .06$) better fit for average psychosocial support, thus indicating that the full model's predictor variables generally made a significant contribution to model fit. The full model for average career support did not fit significantly better than its best fitting change trend model (Model 1c: Quadratic change).

A pseudo-R^2 statistic measures the total amount of variation in outcomes explained by the predictors in a multilevel model (Singer & Willett, 2003), similar to the traditional R^2 statistic, and is calculated as the squared correlation of the predicted and observed measures of a developmental network characteristic for each person at each time point. These pseudo-R^2 statistics enable us to compare the amount of variance explained by our more basic models to those with more predictors for each developmental network characteristic (i.e., from Model 1a through Model 2) as well as to compare the amount of variance explained by the same set of predictors across developmental network characteristics.[6] Tables 3a-3e also report two additional

[6] For instance, the pseudo-R^2 statistic for average career support ranged from .06 – or 6 percent of the variation – for the best fitting change trend model (1c) to .10 – or 10 percent of the variation – for the full model.

pseudo-R^2 statistics for each model: the variation in intercept (R^2 Intercept) and variation in rate of change (R^2 Slope) explained by the model. Note that pseudo-R^2 statistics are not always positive, like traditional R^2 statistics; rather, they can be negative when the outcome variation is primarily within-individual or between-individual (Singer & Willett, 2003).

DISCUSSION

The present study is the first to offer a comprehensive view of the longitudinal change trends of multiple key developmental network characteristics over a substantive amount of time. Specifically, in this ten-year study of developmental networks post-business school, we investigated five developmental network characteristics representing the content of help individuals received and the structure of the ties comprising the network. With this in-depth investigation, we offer discoveries regarding the dynamics of developmental networks that we hope can inform future theory and research. Our discoveries contribute by opening up the black box assumption that individuals' networks and career-based relationships change over time to examine just what those changes are and how they occur as well as some of the factors that may or may not contribute to such change trends.

Specifically, we discovered several notable differences in change trends across the five developmental network characteristics (RQ1): for two characteristics, the best-fitting change trend model was *linear* (average psychosocial support and communication frequency); for two characteristics, it was *quadratic* (average career support and density); and for one characteristic, it was the *no change* model. We also found that all five change trends showed significant variance in the starting levels, but not in change over time.

Regarding covariation of change trends (RQ2), we found that the intercepts of these network characteristics were often correlated with one another. Only two pairs of slopes were correlated with one another, both positively. For these two pairs, average career support with density and closeness with communication frequency, participants' characteristics moved in tandem, such that they both increased or both decreased. It is particularly noteworthy that we did not find that the two types of content, average career and psychosocial support, changed together over time, nor did all types of developmental network structure change with one another. This means that change trends for these characteristics operated independently of one another, rather than moving synchronously or as tradeoffs. We also found that average career support's intercept and slope were least frequently correlated with other intercepts and slopes, suggesting that average career support functioned particularly independently relative to the other characteristics.

We found that network size was the key predictor of the change trends for all five developmental network characteristics (RQ3). It was positively related to starting levels of average career support and density and negatively related to starting levels of average psychosocial support, closeness and communication frequency. However, over time, smaller networks provided more of both types of content (i.e., more average career and psychosocial support), more diversity (i.e., lower density), and stronger ties (i.e., greater closeness and more frequent communication) than larger networks.

Interestingly, we found no clear relationships between the individual or organizational/industry antecedent factors we examined and initial levels of developmental network characteristics. We could not explore predictors of the change trends' slopes because of the lack of significant between-individual variance in the best-fitting models. Moreover, we did not find that factors often theorized in careers research as critical, such as number of employers (Sullivan, 1999), actually impacted network dynamics.

Future Directions for Theory and Research on the Dynamics of Developmental Networks

Our findings cannot be fully explained by existing theory; that is, they raise some theoretical anomalies. Below, we draw on three different theoretical perspectives – mentoring, social network and developmental stages theories – to interpret these findings and to highlight how theory may be used to address the anomalies. Then, we suggest four parameters for future theorizing suggested by our findings. Taken together, these ideas may help to provide the foundation for future theory-building, particularly with the goal of moving closer to having a comprehensive – and *dynamic* – theoretical framework of developmental networks.

Theoretical perspectives regarding current findings.

Mentoring theory. Since their introduction into the management literature, developmental networks have been viewed as a "reconceptualized" form of mentoring (Higgins & Kram, 2001) in which the ties that comprise a network of multiple developers provide mentoring support. As Kram's (1983; 1985) foundational research highlighted, mentoring relationships are themselves dynamic and involve specific phases: initiation, cultivation, separation, and redefinition. Thus, based on mentoring theory, we should expect that developmental networks, which are comprised of mentoring relationships, would also go through dynamic processes. However, mentoring theory cannot explain our results, in terms of specifying change trends beyond the dyadic level. That is, although mentoring theory speaks to the fundamental notion that relationships between a mentor and a mentee change, it provides little insight into the specifics of what these changes might look like. Therefore, additional theoretical perspectives could be helpful in developing a more comprehensive theory.

Social network theory. In addition to mentoring theory, social network theory is the other dominant theory relevant to developmental networks research (Higgins & Kram, 2001). Social network theory argues for the fundamental dynamic nature of networks, both at the network level (e.g., Snijders, 2001, 2009) and at the individual tie level (e.g., Walter et al., 2015), and fortunately has provided the conceptual definitions and methodologies to examine specific characteristics of networks, including the structural characteristics considered here. However, social network research has also called for longitudinal research to bolster and develop theory (e.g., Battilana & Casciaro, 2012; Snijders, 2009). Thus, as with mentoring research, social network theory provides only a partial explanation of our results: it does not speak to the shape of the five developmental network characteristics' change trends; the nature of change in this type of network, as opposed to social networks more generally; nor how the comprehensive set of characteristics' change trends behave when explored simultaneously.

Further, social network theory often emphasizes certain kinds of ties, such as weak ties (Granovetter, 1983; Granovetter, 1973), or that "more is better" when it comes to the connection between network size and outcomes (e.g., Seibert, Kraimer, & Liden, 2001). In our study, participants' developmental networks became smaller over time and, interestingly, protégés with *more* developers received less content on average from their networks by the end of the study and suffered potential costs, in terms of less diversity, less closeness, and less frequent communication. Although our results are surprising in light of the "more is better" view espoused in some social network research and in developmental networks research, they are not as surprising from the perspective of another part of social network theory. In this view, the larger one's network is, the less strong each tie is on average, as it is an almost axiomatic principle in social network research flowing from the idea that building and maintaining ties takes up ego's time (Granovetter, 1983; Granovetter, 1973). Another alternative explanation for our findings is that the relationship between network size and the developmental network characteristics is spurious, due to the nature of eliciting developers' names on the surveys. It could be easy for participants to think of a few "strong" developers first, but then as they spend time trying to think of more people, the people they think of will be, by definition, less strong developers. Thus, there could be a negative relationship between network size and developmental network characteristics, especially closeness and communication frequency, that is noise, rather than a substantive finding. Nonetheless, these perspectives do not fully explain our results, as network size has an overall *positive* relationship with one type of content (i.e., average career support), particularly at the beginning of the study, yet it has a *negative* relationship with the other (i.e., average psychosocial support). Further, we found that larger networks are more dense, which is the opposite of what these alternative views would predict. Lastly, these perspectives do not explain why network size itself decreases over time. We thus recommend that future theory and research focus on understanding network size's role in developmental networks as well as other kinds of help-giving networks, such as advice networks, which are often studied in social network research (e.g., Walter et al., 2015).

Developmental stages theory. The above theories cannot explain why we saw the particular change trend shapes (i.e., no, linear or quadratic change) or direction (i.e., increasing, decreasing, staying the same) for the different developmental network characteristics studied here, nor do they explain when these change trends may occur over the course of people's lives. However, such findings may echo Kegan's (1982, 1994) adult development theory, which suggests that adults go through developmental stages, defined as "a frame of reference that one uses to structure one's world and from within which one perceives the world" (Gallos, 1989: 114), from dependent to independent to inter-independent. Scholars argue that as adults develop from one stage to the next, these transitions should be mirrored in changes in developmental relationships (McGowan, Stone, Kegan, Ragins, & Kram, 2007) and in developmental networks in particular (Chandler & Kram, 2005; Dobrow et al., 2012; Ghosh, Haynes, & Kram, 2013).

For instance, Chandler and Kram (2005) proposed, but did not empirically investigate, the idea that protégés in the interpersonal stage of adult development (Kegan, 1982, 1994) should have more diverse (i.e., less dense) networks. Our findings showed this general trend that networks became less dense over time, albeit with a quadratic shape not predicted by theory. However, developmental stages theory does not provide predictions for specific changes in developmental networks and so, while helpful, cannot explain our full set of discoveries offered here. Moreover, this theory does not explain why beginnings are so important, as we found here with respect to the variance in the intercepts of developmental network characteristics. Therefore, a comprehensive framework of developmental network change could build on developmental stages theory and the discoveries shared here to theorize about if and for how long changes in adult development may be reflected in changes in one's developmental network – especially during early career when individuals are most susceptible to the influence of significant others (e.g., Levinson, 1986).

Parameters for future theorizing. We propose that any comprehensive theory about the dynamics of developmental networks consider the following dimensions highlighted by the discoveries shared here: multiple characteristics of developmental networks, the inner workings of developmental networks, factors impacting developmental networks, and time.

Multiple characteristics of developmental networks. Seibert and colleague's (2001) "social capital theory of career success" sheds light on the power of conducting research on multiple aspects of social networks' structure and resources. Our work confirms the value of such a theoretical perspective. For instance, regarding the three structural characteristics we studied, participants with smaller networks had less tight-knit networks (i.e., lower density) that were nonetheless characterized by stronger ties (i.e., higher average closeness and communication frequency). This contrast between the density and tie strength results suggests that participants had an intriguing mix of structural characteristics in their developmental networks: those with smaller networks likely benefited from the diversity that came from their less dense networks, such that they obtained access to more diverse information. Yet, when it came to the strength of the ties in these smaller networks, rather than gain access to even more diverse information via the weak ties that might be expected in a lower density network, participants instead had *stronger* ties and the different benefits that went along with those (e.g., emotional closeness, solidarity; see Granovetter, 1983; Granovetter, 1973; Nelson, 1986). Given our findings here and Seibert and colleagues' (2001) findings, we suggest that any comprehensive theory consider multiple aspects of both the content and structure of developmental networks and how they interrelate with one another over time. Although mentoring research has largely focused on tie content (i.e., the kind of help provided) and while social network research has largely emphasized network structure, our work brings these dimensions together, which we suggest is warranted in future theory-building and empirical research as well.

Inner workings of developmental networks. Our exploratory findings also suggest that beyond content and structure, theory might also evolve to consider in greater depth the inner workings of developmental networks. For instance, by drawing on recent research highlighting the importance of reconnecting to long-lost, dormant ties in social networks (Walter et al., 2015), future research could develop theory regarding how and why specific ties come and go, and the value that these ties do or do not provide to protégés. As our results showed that average tie strength in networks shifted over time, it would be useful to theorize about why such changes occur. For example, theory could incorporate insights from related fields, such as social support, that has long distinguished between instrumental and expressive forms of help but has rarely considered these aspects over time (e.g., Zimet, Dahlem, Zimet, & Farley, 1988).

Future theoretical work might also incorporate ideas from research on high-quality connections (Dutton, 2003; Dutton & Heaphy, 2003). One type of high-quality connection is a high-quality mentoring relationship, which “promotes mutual growth, learning and development within the career context” (Fletcher & Ragins, 2007: 374). As high-quality connections lead to outcomes such as increased self-awareness, self-esteem, new skills, zest, a desire for more connection, and well-being (Dutton & Heaphy, 2003; Fletcher & Ragins, 2007), future developmental networks research could apply this theoretical perspective to the inner workings of these networks. Thus, future work might explore questions such as how long high-quality connections must exist in a network before they can have a positive effect; whether there is a time lag between the formation of these relationships and their impact; and whether different connections come and go from one’s network and if so, how (cf. Walter et al., 2015).

In tandem with such theoretical inquiry, we encourage methodological advances to enable 3-level multilevel analyses that would allow for a closer examination of the inner workings of developmental networks, specifically to examine time periods (level 1) nested within developers (level 2) nested within the protégé’s developmental network (level 3). This statistical approach does not exist at present (as noted in Wu, Parker, & Jong, 2014). However, we hope the opportunity to build on this study and develop theory might create demand and motivation for such advances, which could prove valuable and so extend the present research.

Factors related to developmental networks. The predominance of null findings among the individual- and organizational/industry-level predictors studied here suggests the need to expand our theoretical and empirical inquiry into antecedents. The literatures on feedback-seeking (Ashford & Northcraft, 1992; Levy, Albright, Cawley, & Williams, 1995; Li et al., 2011) and help-seeking (see Bamberger, 2009, for a review), both of which are foundational elements for developmental network cultivation, have shown that different factors impact the extent to which people seek out help. For example, individual-level factors such as perceptions of evaluation during a learning task (Higgins, 2001a), shyness (DePaulo, Dull, Greenberg, & Swaim, 1989), and gender (Baugh, Lankau, & Scandura, 1996) have been associated with lower levels of help-seeking. Of these variables, our study included only gender. Future research could extend this work by considering, for example, proactive personality (Singh, Ragins, & Tharenou, 2009a), relational savvy (Chandler, 2009), stages of adult development (see Chandler, Kram, & Yip, 2011 for a review), emotional intelligence (Cherniss, 2007), self-monitoring (Kim & Kim, 2007), and work orientations (Tschopp, Unger, & Grote, 2016). We hope future developmental network research will also consider individual-level factors associated with developers and the match between protégés and developers so that we can better understand how these networks evolve.

Temporal characteristics of developmental networks. Our study encourages future theorizing and empirical work regarding the role of time in organizational and management research – that is, how time is conceptualized and empirically considered (e.g., George & Jones, 2000; Mitchell & James, 2001; Wright, 1997; Zaheer, Albert, & Zaheer, 1999). Indeed, a major contribution of our study is its exploration of developmental network characteristics over a long amount of time, which can lead to substantively different results than cross-sectional or short-term study designs. As one example, whereas previous research found that, on average, developmental network density increased over the span of two years, as calculated with a difference score (Dobrow & Higgins, 2005), the present study found that density did initially increase for a few years, but then *declined* in a curvilinear fashion. The present results could only have been discovered using a long-term perspective and appropriate statistical techniques.

Additionally, given our findings regarding the significant variance among the intercepts of developmental network characteristics, we advocate that future theory-building thoughtfully consider the importance of the “beginnings” of these networks. A focus on beginnings can be found in prior research at the individual, team, and organization levels, including social psychological research on person perception, where studies have repeatedly demonstrated that perceptions result from thin slices of information that impact outcomes such as judgment and decision-making later on (e.g., Ambady & Rosenthal, 1993). At the team level, Hackman (2012) demonstrated how the initial conditions of a team’s work in multiple settings can significantly shape team effectiveness. At the organization level, research has demonstrated that “getting off to a good start,” for example, in terms of the social capital an organization possesses, can yield positive returns over time (e.g., Higgins & Gulati, 2003). We thus encourage that future theorizing about developmental networks incorporate the importance of these networks’ beginnings, especially at pivotal career development junctures (e.g., starting one’s career).

In contrast to the significant between-individuals variance in intercepts, the lack of variance in slopes inhibited our examination of slopes’ predictors. These results suggest the suprising interpretation that everyone experiences somewhat similar rates of change for their developmental network characteristics. However, we encourage future research to replicate these results and develop theory that might explain why people experience such similiarity. This study’s discoveries point to a more sophisticated perspective on temporal research – beyond considering before and after states to a perspective that disentangles critical components of time such as initial conditions (as indexed by an intercept) along with rates of change (slopes) and change trends (both linear and more complex shapes). Moreover, as researchers begin to delineate predictors of developmental networks' intercepts and slopes, we encourage the exploration of patterns between the two – for example, whether a predictor helps individuals get off to both a stronger start and experience a positive change over time, whether it helps individuals get off to a stronger start but then experience a negative change over time, or some other combination (Song et al., 2017).

Practical Implications

Our exploratory study suggests implications for both individuals navigating their careers and for managers who are charged with helping early-career individuals do so. Individuals may benefit from insights about if and how their developmental networks might change over time by treating these relationships as growing, adapting phenomena that need thoughtful attention and cultivation. They can thus proactively and/or intentionally shape and maintain their developmental networks over time to foster career development (Chandler, 2009) and more beneficial career outcomes (Seibert et al., 2001). For instance, our findings regarding network size suggest that, overall, smaller networks are associated with levels of developmental network characteristics that typically lead to more beneficial outcomes. Indeed, our participants struck an unexpected and interesting balance with the structural characteristics in their developmental networks, such that those with smaller networks not only had less dense networks but also stronger ties. Thus, individuals can be mindful of keeping their network size smaller, rather than assuming that "more is better," as well as considering the potential tradeoffs they can make with their networks to obtain their desired outcomes.

Organizations can benefit from the recognition that people's developmental networks can be expected to shift over time by encouraging people to proactively and thoughtfully cultivate and manage their developmental networks, rather than assume they will remain stable over time. Organizations can aim to use people's changing developmental networks in conjunction with internal development programs, including formal mentoring programs or other means to foster positive workplace relationships (Ferris et al., 2009). Additionally, through recognizing the changes that occur in individuals' developmental networks, organizations can strive to provide more tailored, flexible developmental support. For instance, given that smaller networks were associated with higher levels of average career and psychosocial support, organizations can seek to maintain or even strengthen their employees' capacity to engage with a relatively smaller number of "high-quality" developers, both inside and outside the organization.

Limitations

Our sample came from a single cohort of graduating MBA students from the same business school. Given the relative homogeneity of this population in terms of education and profession, we might have expected individuals' developmental network change trajectories to be similar to one another. Rather, we found significant variance in intercepts and different types of change trajectories based on developmental network size. Yet we did not find significant variance in slope, which could either reflect a consistent type of change experienced by adults in general or could be specific to this sample, and so, should be replicated in a more diverse sample. Future work that explores developmental network dynamics in a broader range of educational and professional contexts would extend the present research.

We view our longitudinal dataset comprised of complete developmental networks over a 10-year timeframe as a core strength of our study; however, this design also limits our study. Our examination of predictors of developmental network trajectories was, by necessity, limited to the measures on our Time 1 survey many years ago. As such, we could not investigate more recently published measures as predictors. Our study thus achieves an important goal of providing a fundamental, exploratory picture of developmental networks' change trends and predictors over an extended timeframe, but it cannot provide as up-to-date an account of predictors of developmental network characteristics as could a longitudinal study begun today. Nevertheless, our null findings regarding predictors suggest that certain plausible explanations, such as individual-level characteristics like gender and ethnicity or an organization-level characteristic like number of employers, may likely be ruled out. In an abductive reasoning framework, this is helpful by virtue of narrowing the set of potential predictors and helping direct researchers to alternative explanatory factors (as suggested above) that may yield more robust effects (Bamberger & Ang, 2016; Miller & Bamberger, 2016). We view the study of predictors of developmental network characteristics as a key avenue for future research.

CONCLUSION

This study offers the first comprehensive look at the dynamics of developmental networks over a substantial timeframe of ten years. Our discoveries highlight the significance of beginnings, or the ways in which individuals' networks start off as they launch their post-graduate careers; the significance of network size, for which we found that more is not necessarily better – that smaller networks can, over time, yield benefits to individuals in terms of greater content provided by the network, greater network diversity and stronger ties; and the significance of nonlinear change trends in network characteristics that can play out in unpredictable and interrelated ways. We are hopeful that our investigation into the characteristics of both developmental network content and structure in this study will pique the interest of mentoring, developmental networks, careers, and management scholars who have long suggested that relationships evolve and that career and adult development occur over time, but have hesitated to delve deeply into this research, particularly empirically. Here, by providing an in-depth examination into just what those change dynamics might look like, by offering theoretical insights and directions for research on such dynamics, and by providing a methodological approach for studying network dynamics, we hope to inspire others to build theory and develop the empirical capacity to engage in this work.

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TABLE 1

Overview of Measures Used in the Analyses

Variables	**Source**			
	Time 1	Time 2	Time 3	Time 4
Predictor Variables				
Gender	X			
Ethnicity	X			
Marital status (time-varying)	X	X	X	X
Citizenship	X			
Years of work experience (pre-MBA)	X			
Industry prior to MBA program: Financial services	X			
Industry prior to MBA program: Consulting	X			
Industry prior to MBA program: Technology	X			
Network size	X	X	X	X
Number of employers	X	X	X	X
Dependent Variables[a]				
Developmental Network Content				
Average career support	X	X	X	X
Average psychosocial support	X	X	X	X
Developmental Network Structure				
Density	X	X	X	X
Closeness	X	X	X	X
Communication frequency	X	X	X	X
Additional Analyses				
Sum career support	X	X	X	X
Sum psychosocial support	X	X	X	X

Note. [a]Participants with one, two, three, or all four measures of this developmental network measure can be included in multilevel analyses.

TABLE 2

Descriptive Statistics and Correlations among the Study Variables[a]

	Variable	*X*	*SD*	1	2	3	4	5	6	7	8	9	10
1.	Gender	0.27	0.45										
2.	Ethnicity	0.24	0.43	-0.02									
3.	Marital status: Time 1	0.32	0.47	-0.13	-0.08								
4.	Marital status: Time 2	0.57	0.50	-0.11	-0.17	0.62 **							
5.	Marital status: Time 3	0.71	0.46	0.02	-0.15	0.35 **	0.61 **						
6.	Marital status: Time 4	0.88	0.33	-0.01	0.18	0.23	0.33 **	0.53 **					
7.	Citizenship	0.34	0.48	-0.12	0.17	0.05	0.17	0.05	-0.01				
8.	Years of work experience (pre-MBA)	3.74	1.86	-0.11	0.04	0.33 **	0.21 *	0.00	0.09	0.00			
9.	Industry prior to MBA program: Financial services	0.28	0.45	-0.12	-0.11	0.04	0.07	0.21 *	0.15	-0.13	-0.18 *		
10.	Industry prior to MBA program: Consulting	0.23	0.42	0.23 **	0.12	-0.06	-0.12	-0.01	-0.06	0.03	-0.15	-0.34 **	
11.	Industry prior to MBA program: Technology	0.05	0.21	-0.14	0.14	-0.07	-0.08	-0.24 *	0.08	0.07	-0.05	-0.14	-0.12
12.	Number of employers (Time 1 to Time 4)	3.45	1.14	-0.12	0.08	0.07	-0.12	-0.33 *	-0.10	-0.03	-0.01	-0.04	0.06
13.	Network size: Time 1	4.30	1.21	0.00	-0.09	0.03	-0.01	0.03	-0.17	-0.05	0.08	-0.06	0.12
14.	Network size: Time 2	4.05	1.25	-0.08	-0.13	0.10	-0.04	0.07	0.01	-0.19	0.19	0.04	-0.02
15.	Network size: Time 3	3.83	1.41	-0.18	-0.23 *	0.06	-0.04	0.09	-0.10	-0.17	-0.04	0.06	0.09
16.	Network size: Time 4	3.50	1.48	-0.03	0.13	0.05	-0.18	-0.10	-0.03	-0.10	-0.01	0.01	-0.01
17.	Average career support: Time 1	3.45	1.31	0.07	0.15	-0.01	-0.03	-0.03	-0.04	0.06	-0.09	0.01	-0.03
18.	Average career support: Time 2	3.94	1.39	-0.05	0.05	0.10	-0.12	0.06	-0.14	0.07	-0.06	-0.01	-0.08
19.	Average career support: Time 3	4.05	1.25	0.25 *	-0.11	0.08	0.08	0.10	-0.20	-0.10	-0.07	0.14	-0.05
20.	Average career support: Time 4	4.37	1.16	0.23	-0.03	-0.02	0.06	0.04	-0.23	-0.15	-0.14	0.04	-0.08
21.	Average psychosocial support: Time 1	5.62	0.91	0.03	0.04	-0.11	-0.15	-0.11	0.22	-0.23 **	-0.02	-0.04	0.01
22.	Average psychosocial support: Time 2	5.51	0.98	0.10	-0.06	-0.04	-0.01	0.04	0.20	-0.19 *	-0.12	0.09	-0.04
23.	Average psychosocial support: Time 3	5.68	0.89	0.16	0.02	-0.02	0.07	0.08	0.08	-0.18	-0.15	0.17	-0.10
24.	Average psychosocial support: Time 4	5.68	0.75	0.03	0.04	0.04	0.13	0.18	0.42 **	-0.13	-0.10	0.25 *	-0.18
25.	Density: Time 1	0.55	0.31	-0.11	0.03	0.09	0.07	0.23 *	0.22	-0.09	-0.04	0.01	0.18 *
26.	Density: Time 2	0.67	0.29	0.13	-0.09	0.15	0.13	0.21	0.09	0.06	-0.20 *	0.07	0.15
27.	Density: Time 3	0.60	0.35	0.03	-0.07	-0.07	-0.03	0.24 *	0.19	-0.13	-0.10	0.06	0.20
28.	Density: Time 4	0.24	0.35	-0.05	0.14	0.02	-0.15	-0.01	-0.11	-0.02	0.05	-0.03	-0.04
29.	Closeness: Time 1	3.39	0.43	-0.05	0.04	0.05	0.00	-0.01	0.19	-0.27 **	0.06	0.01	0.09
30.	Closeness: Time 2	3.43	0.46	0.16	0.04	-0.14	-0.15	-0.04	0.15	-0.18	-0.15	0.14	0.00
31.	Closeness: Time 3	3.54	0.38	0.08	0.08	-0.09	0.05	-0.06	-0.04	-0.04	-0.06	0.20	-0.20
32.	Closeness: Time 4	3.47	0.46	0.02	0.12	-0.09	-0.02	0.12	0.25 *	-0.11	-0.20	0.26 *	-0.02
33.	Communication frequency: Time 1	0.55	0.20	-0.02	-0.14	-0.02	0.05	0.01	0.12	-0.20 *	-0.13	0.00	0.14
34.	Communication frequency: Time 2	0.59	0.21	-0.01	-0.12	-0.14	0.11	0.21	0.04	-0.07	-0.25 *	0.19	0.00
35.	Communication frequency: Time 3	0.64	0.20	-0.17	-0.05	-0.12	0.08	0.06	-0.05	-0.02	0.02	0.00	-0.03
36.	Communication frequency: Time 4	0.66	0.21	0.07	-0.03	-0.14	0.04	0.00	0.27 *	-0.03	0.02	-0.08	0.22

Note. [a]Pairwise correlations resulted in a range of $n = 43$ to $n = 131$.
* $p < .05$
** $p < .01$

TABLE 2, cont.

	Variable	11	12	13	14	15	16	17	18	19	20	21	22
12.	Number of employers (Time 1 to Time 4)	0.18											
13.	Network size: Time 1	-0.08	0.08										
14.	Network size: Time 2	-0.15	0.11	0.49 **									
15.	Network size: Time 3	-0.20	0.10	0.28 **	0.52 **								
16.	Network size: Time 4	0.06	0.13	0.20	0.26 *	0.41 **							
17.	Average career support: Time 1	0.19 *	0.13	0.26 **	0.12	0.16	0.24 *						
18.	Average career support: Time 2	0.07	-0.09	0.02	-0.03	0.05	0.12	0.34 **					
19.	Average career support: Time 3	-0.25 *	-0.01	0.24 *	0.18	0.16	0.18	0.31 **	0.47 **				
20.	Average career support: Time 4	-0.12	-0.13	0.10	0.11	-0.11	-0.11	0.27 *	0.37 **	0.28 *			
21.	Average psychosocial support: Time 1	0.11	0.27 *	-0.06	0.15	0.11	0.15	0.28 **	-0.03	-0.02	-0.01		
22.	Average psychosocial support: Time 2	0.11	0.06	-0.14	-0.24 *	-0.04	0.07	0.24 *	0.01	0.13	0.00	0.61 **	
23.	Average psychosocial support: Time 3	-0.17	-0.06	0.06	-0.08	-0.07	0.11	0.20	0.21	0.40 **	0.02	0.38 **	0.65 **
24.	Average psychosocial support: Time 4	-0.02	-0.09	0.02	-0.12	-0.39 **	-0.08	0.18	0.02	0.16	0.12	0.30 *	0.49 **
25.	Density: Time 1	0.01	0.05	0.22 *	0.06	-0.01	-0.17	-0.09	-0.09	-0.12	-0.20	0.16	0.25 **
26.	Density: Time 2	-0.08	-0.07	-0.06	0.04	0.18	-0.07	-0.07	0.08	0.18	-0.11	0.12	0.18
27.	Density: Time 3	-0.27 *	-0.12	0.07	0.32 **	0.50 **	0.09	0.12	0.14	0.16	-0.06	0.04	-0.12
28.	Density: Time 4	-0.12	-0.05	0.16	0.10	0.37 **	0.72 **	0.30 *	0.16	0.19	-0.02	0.10	0.15
29.	Closeness: Time 1	0.04	0.14	-0.33 **	0.01	0.13	0.04	-0.07	-0.10	-0.08	-0.19	0.56 **	0.43 **
30.	Closeness: Time 2	0.09	0.02	-0.11	-0.22 *	-0.12	0.13	0.15	-0.06	0.10	-0.03	0.52 **	0.75 **
31.	Closeness: Time 3	0.05	0.03	-0.17	-0.21	-0.20	0.00	0.12	0.13	0.04	0.13	0.30 **	0.51 **
32.	Closeness: Time 4	0.01	-0.05	0.03	-0.08	-0.16	-0.12	0.17	-0.01	0.16	-0.04	0.22	0.28 *
33.	Communication frequency: Time 1	0.06	-0.02	-0.19 *	-0.08	0.03	0.00	-0.20 *	-0.26 **	-0.32 **	-0.25 *	0.35 **	0.34 **
34.	Communication frequency: Time 2	0.06	-0.16	-0.19	-0.32 **	-0.14	-0.19	0.04	-0.01	0.00	-0.04	0.16	0.43 **
35.	Communication frequency: Time 3	0.16	-0.01	-0.13	-0.08	-0.16	0.10	0.00	0.09	0.01	-0.04	0.11	0.26 *
36.	Communication frequency: Time 4	0.00	-0.07	-0.11	-0.06	-0.21	-0.39 **	-0.11	-0.11	-0.23	-0.06	0.10	0.09

	Variable	23	24	25	26	27	28	29	30	31	32	33	34	35
24.	Average psychosocial support: Time 4	0.52 **												
25.	Density: Time 1	0.09	0.08											
26.	Density: Time 2	0.08	0.02	0.27 **										
27.	Density: Time 3	0.03	-0.07	0.25 *	0.40 **									
28.	Density: Time 4	0.18	0.00	-0.18	-0.13	0.06								
29.	Closeness: Time 1	0.12	0.07	0.33 **	0.28 **	0.03	0.03							
30.	Closeness: Time 2	0.60 **	0.40 **	0.19	0.08	-0.12	0.20	0.36 **						
31.	Closeness: Time 3	0.64 **	0.41 **	0.07	0.02	-0.01	0.14	0.15	0.54 **					
32.	Closeness: Time 4	0.36 *	0.63 **	-0.06	0.07	0.09	-0.12	0.09	0.17	0.29 *				
33.	Communication frequency: Time 1	0.00	0.18	0.29 **	0.35 **	-0.01	-0.02	0.48 **	0.37 **	0.01	0.21			
34.	Communication frequency: Time 2	0.11	0.08	0.23 *	0.22 *	0.04	-0.14	0.20 *	0.39 **	0.08	-0.13	0.30 **		
35.	Communication frequency: Time 3	0.21	0.19	0.15	0.00	0.13	0.09	0.08	0.26 *	0.35 **	0.16	0.26 *	0.39 **	
36.	Communication frequency: Time 4	-0.06	0.30 *	0.07	-0.01	0.08	-0.36 **	0.07	0.10	-0.02	0.30 *	0.28 *	0.12	0.20

TABLE 3a

Multilevel Models for the Five Developmental Network Characteristics: Average Career Support

	Model 1a: No change			Model 1b: Linear change			Model 1c: Quadratic change			Model 1d: Cubic change			Model 2: Full			Supplementary Model: Full + Number of Employers		
Parameter	Estimate		Std. Error	Estimate		Std. Error	Estimate		Std. Error	Estimate		Std. Error	Estimate		Std. Error	Estimate		Std. Error
Intercept	4.23	***	0.24	3.55	***	0.25	3.47	***	0.26	3.18	***	0.27	2.72	***	0.51	1.74	*	0.79
<u>Predictors</u>																		
Gender													0.32		0.20	0.36		0.31
Ethnicity													0.25		0.21	0.83	*	0.35
Marital status (time-varying)													-0.12		0.16	0.19		0.25
Citizenship													0.01		0.19	0.27		0.29
Years of work experience (pre-MBA)													-0.05		0.05	-0.06		0.08
Industry prior to MBA program: Financial services													0.04		0.22	0.48		0.34
Industry prior to MBA program: Consulting													-0.37		0.23	-0.36		0.35
Industry prior to MBA program: Technology													0.22		0.46	-0.52		0.74
Number of employers																0.06		0.12
Network size	-0.09		0.05	0.00		0.05	0.00		0.05	0.06		0.06	0.21	*	0.10	0.28	*	0.13
Network size x Years													-0.04		0.05	-0.08		0.07
Network size x Years x Years													0.00		0.00	0.01		0.01
<u>Time</u>																		
Linear Time: Years				0.09	***	0.02	0.20	***	0.06	0.42	**	0.13	0.41	*	0.21	0.56	t	0.29
Quadratic Time: Years x Years							-0.01	*	0.01	-0.08	*	0.03	-0.02		0.02	-0.04		0.03
Cubic Time: Years x Years x Years										0.00	*	0.00						
<u>Pseudo R^2 Statistics and Goodness-of-fit</u>																		
Pseudo R^2 Overall model					.05			.06			.07			.10			.13	
Pseudo R^2 Intercept								.19			-.96			.33			.49	
Pseudo R^2 Slope								-10.91			-510.29			-15.30			-6.38	
Deviance (-2 Log Likelihood)		1257.90			1232.68			1220.88			1301.49			1207.92			772.62	

Notes. Number of observations in Models 1a, 1b, 1c, 1d and 2 = 378; number of individuals = 129. Number of observations in Supplementary Model = 203; number of individuals = 62.

[t] $p < .10$

* $p < .05$

** $p < .01$

*** $p < .001$

Field Code Changed

TABLE 3b

Multilevel Models for the Five Developmental Network Characteristics: Average Psychosocial Support

	Model 1a: No change			Model 1b: Linear change			Model 1c: Quadratic change			Model 1d: Cubic change			Model 2: Full			Supplementary Model: Full + Number of Employers		
Parameter	Estimate		Std. Error	Estimate		Std. Error	Estimate		Std. Error	Estimate		Std. Error	Estimate		Std. Error	Estimate		Std. Error
Intercept	6.13	***	0.15	6.06	***	0.17	6.06	***	0.16	6.22	***	0.18	6.25	***	0.31	6.24	***	0.48
Predictors																		
Gender													0.18		0.14	0.29		0.19
Ethnicity													0.06		0.15	0.57	*	0.21
Marital status (time-varying)													0.16		0.10	0.32	*	0.13
Citizenship													-0.41	**	0.13	-0.38	*	0.18
Years of work experience (pre-MBA)													-0.04		0.04	-0.11	*	0.05
Industry prior to MBA program: Financial services													0.05		0.16	0.06		0.21
Industry prior to MBA program: Consulting													-0.17		0.16	-0.21		0.21
Industry prior to MBA program: Technology													-0.01		0.33	-0.35		0.41
Number of employers																0.03		0.07
Network size	-0.13	***	0.03	-0.12	**	0.03	-0.11	**	0.03	-0.14	***	0.04	-0.11	*	0.05	-0.11		0.07
Network size x Years													0.00		0.01	0.00		0.01
Network size x Years x Years																		
Time																		
Linear Time: Years				0.01		0.01	-0.03		0.03	-0.15	*	0.07	0.00		0.03	-0.03		0.04
Quadratic Time: Years x Years							0.00		0.00	0.04	*	0.02						
Cubic Time: Years x Years x Years										0.00	t	0.00						
Pseudo R^2 Statistics and Goodness-of-fit																		
Pseudo R^2 Overall model				.02			.02			.02			.07			.17		
Pseudo R^2 Intercept							-.03			-.32			.04			.08		
Pseudo R^2 Slope							-19.69			-169.94			-.20			-.16		
Deviance (-2 Log Likelihood)	886.55			879.31			886.73			905.00			862.94			451.80		

Notes. Number of observations in Models 1a, 1b, 1c, 1d and 2 = 379; number of individuals = 129. Number of observations in Suplementary Model = 203; number of individuals = 62.

t $p < .10$

* $p < .05$

** $p < .01$

*** $p < .001$

Field Code Changed

TABLE 3c

Multilevel Models for the Five Developmental Network Characteristics: Density

Parameter	Model 1a: No change		Model 1b: Linear change		Model 1c: Quadratic change		Model 1d: Cubic change		Model 2: Full		Supplementary Model: Full + Number of Employers	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Intercept	0.14 *	0.05	0.24 ***	0.06	0.17 **	0.06	0.33	0.06	0.43 ***	0.10	0.45 **	0.15
Predictors												
Gender									-0.03	0.04	-0.01	0.05
Ethnicity									0.02	0.04	0.00	0.05
Marital status (time-varying)									0.08 *	0.03	0.13 **	0.05
Citizenship									-0.01	0.03	0.05	0.04
Years of work experience (pre-MBA)									-0.02 ^{t}	0.01	-0.02 ^{t}	0.01
Industry prior to MBA program: Financial services									-0.01	0.04	-0.05	0.05
Industry prior to MBA program: Consulting									0.08 ^{t}	0.04	0.06	0.05
Industry prior to MBA program: Technology									-0.12	0.09	-0.27 *	0.10
Number of employers											-0.01	0.02
Network size	0.10 ***	0.01	0.09 ***	0.01	0.09 ***	0.01	0.05	0.01	0.04 *	0.02	0.04	0.03
Network size x Years									0.00	0.01	-0.01	0.01
Network size x Years x Years									0.00	0.00	0.00	0.00
Time												
Linear Time: Years			-0.02 ***	0.00	0.07 ***	0.01	0.11	0.03	0.04	0.04	0.08	0.06
Quadratic Time: Years x Years					-0.01 ***	0.00	-0.02	0.01	-0.01 **	0.00	-0.02 **	0.01
Cubic Time: Years x Years x Years							0.00	0.00				
Pseudo R^2 Statistics and Goodness-of-fit												
Pseudo R^2 Overall model			.19		.27		.27		.35		.44	
Pseudo R^2 Intercept					.00		1.00		.13		.05	
Pseudo R^2 Slope					-4.64		1.00		-10.24		-29.51	
Deviance (-2 Log Likelihood)	218.49		192.47		136.43		453.59		96.54		34.70	

Notes. Number of observations in Models 1a, 1b, 1c, 1d and 2 = 386; number of individuals = 131. Number of observations in Supplementary Model = 206; number of individuals = 62.

^{t} $p < .10$
* $p < .05$
** $p < .01$
*** $p < .001$

Field Code Changed

TABLE 3d

Multilevel Models for the Five Developmental Network Characteristics: Closeness

Field Code Changed

	Model 1a: No change			Model 1b: Linear change			Model 1c: Quadratic change			Model 1d: Cubic change			Model 2: Full			Supplementary Model: Full + Number of Employers		
Parameter	Estimate		Std. Error	Estimate		Std. Error	Estimate		Std. Error	Estimate		Std. Error	Estimate		Std. Error	Estimate		Std. Error
Intercept	3.85	***	0.07	3.80	***	0.08	3.78	***	0.09	3.76	***	0.09	3.97	***	0.15	3.87	***	0.22
Predictors																		
Gender													0.04		0.06	0.00		0.08
Ethnicity													0.04		0.06	0.08		0.09
Marital status (time-varying)													0.00		0.05	0.10		0.07
Citizenship													-0.18	**	0.06	-0.13	t	0.08
Years of work experience (pre-MBA)													-0.01		0.02	-0.04	t	0.02
Industry prior to MBA program: Financial services													0.11		0.07	0.09		0.09
Industry prior to MBA program: Consulting													0.04		0.07	0.11		0.09
Industry prior to MBA program: Technology													0.15		0.14	0.16		0.18
Number of employers																0.03		0.03
Network size	-0.10	***	0.02	-0.09	***	0.02	-0.09	***	0.02	-0.08	***	0.02	-0.13	***	0.03	-0.12	**	0.04
Network size x Years													0.01	t	0.00	0.01		0.01
Network size x Years x Years																		
Time																		
Linear Time: Years				0.01		0.01	0.03		0.02	-0.02		0.04	-0.02		0.02	-0.02		0.02
Quadratic Time: Years x Years							0.00		0.00	0.01		0.01						
Cubic Time: Years x Years x Years										0.00		0.00						
Pseudo R^2 Statistics and Goodness-of-fit																		
Pseudo R^2 Overall model					.07			.07			.07			.14			.14	
Pseudo R^2 Intercept								-.07			-1.20			.14			.01	
Pseudo R^2 Slope								-7.71			-190.18			.01			-.75	
Deviance (-2 Log Likelihood)		377.13			371.11			367.19			357.62			351.78			195.48	

Notes. Number of observations in Models 1a, 1b, 1c, 1d and 2 = 380; number of individuals = 129. Number of observations in Supplementary Model = 204; number of individuals = 62.

^{t} $p < .10$

* $p < .05$

** $p < .01$

*** $p < .001$

TABLE 3e

Multilevel Models for the Five Developmental Network Characteristics: Communication Frequency

	Model 1a: No change			Model 1b: Linear change			Model 1c: Quadratic change			Model 1d: Cubic change			Model 2: Full			Supplementary Model: Full + Number of Employers		
Parameter	Estimate		Std. Error	Estimate		Std. Error	Estimate		Std. Error	Estimate		Std. Error	Estimate		Std. Error	Estimate		Std. Error
Intercept	0.80	***	0.04	0.75	***	0.04	0.75	***	0.04	0.76	***	0.04	0.81	***	0.07	0.79	***	0.10
<u>Predictors</u>																		
Gender													-0.04		0.03	0.00		0.04
Ethnicity													-0.05	t	0.03	-0.06		0.04
Marital status (time-varying)													0.05	*	0.02	0.08	*	0.03
Citizenship													-0.07	**	0.03	-0.05		0.03
Years of work experience (pre-MBA)													-0.01	t	0.01	-0.01		0.01
Industry prior to MBA program: Financial services													0.00		0.03	0.02		0.04
Industry prior to MBA program: Consulting													0.06	*	0.03	0.08	t	0.04
Industry prior to MBA program: Technology													0.10		0.06	0.10		0.08
Number of employers																0.00		0.01
Network size	-0.05	***	0.01	-0.04	***	0.01	-0.05	***	0.01	-0.05	***	0.01	-0.04	***	0.01	-0.04	*	0.02
Network size x Years													0.00		0.00	0.00		0.00
Network size x Years x Years																		
<u>Time</u>																		
Linear Time: Years				0.01	**	0.00	0.01		0.01	0.01		0.02	0.01		0.01	0.00		0.01
Quadratic Time: Years x Years							0.00		0.00	0.00		0.01						
Cubic Time: Years x Years x Years										0.00		0.00						
<u>Pseudo R^2 Statistics and Goodness-of-fit</u>																		
Pseudo R^2 Overall model				.11			.11			.11			.18			.18		
Pseudo R^2 Intercept							-.09			-2.02			.30			.33		
Pseudo R^2 Slope							-520.67			-13709.67			1.00			-2.00		
Deviance (-2 Log Likelihood)	-190.72			-198.00			-200.24			-199.24			-222.53			-122.98		

Notes. Number of observations in Models 1a, 1b, 1c, 1d and 2 = 378; number of individuals = 129. Number of observations in Supplementary Model = 202; number of individuals = 62.

t $p < .10$

* $p < .05$

** $p < .01$

*** $p < .001$

TABLE 4

Correlations among Intercepts and Slopes of Developmental Network Characteristics

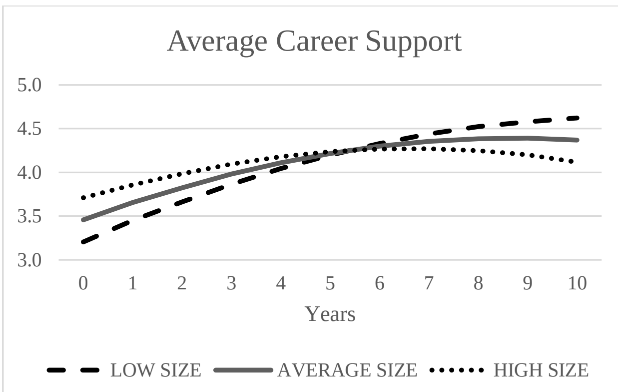
		NETWORK CONTENT				NETWORK STRUCTURE				
	Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1.	Average career support: Intercept									
2.	Average career support: Slope	-0.47 **								
3.	Average psychosocial support: Intercept	0.29 **	-0.08							
4.	Average psychosocial support: Slope	-0.14	0.07	-0.48 **						
5.	Density: Intercept	-0.07	-0.06	0.18	-0.19 *					
6.	Density: Slope	-0.10	0.28 **	-0.08	0.00	-0.54 **				
7.	Closeness: Intercept	0.03	-0.11	0.65 **	-0.21 *	0.30 **	-0.28 **			
8.	Closeness: Slope	0.08	0.00	-0.22 *	0.18	-0.18	0.16	-0.59 **		
9.	Communication frequency: Intercept	-0.15	-0.10	0.40 **	-0.14	0.28 **	-0.11	0.57 **	-0.29 **	
10.	Communication frequency: Slope	0.19 *	-0.07	-0.10	0.07	-0.01	-0.01	-0.25 **	0.36 **	-0.45 **

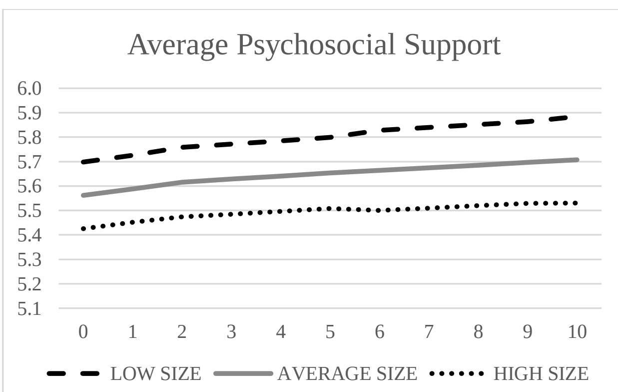
Note. [a]Pairwise correlations resulted in range of $n = 88$ to $n = 116$.
* $p < .05$
** $p < .01$

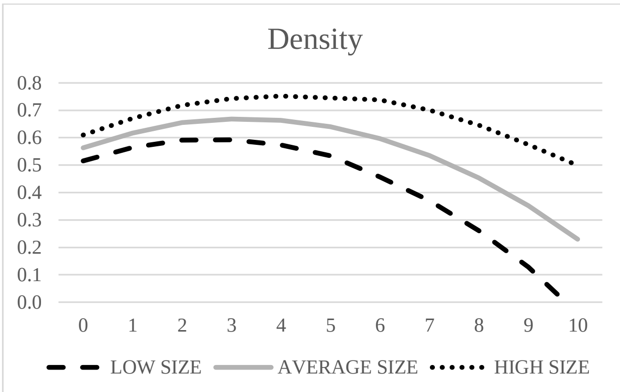
Field Code Changed

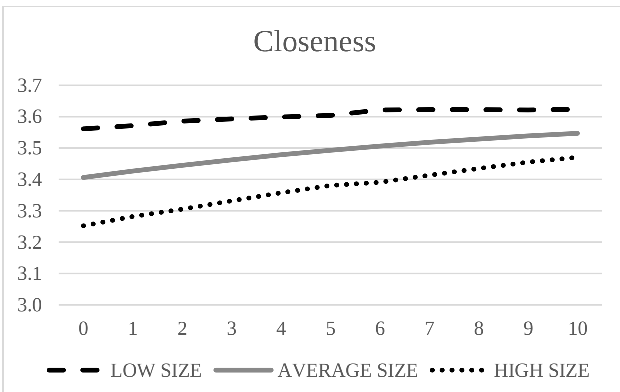
FIGURE 1

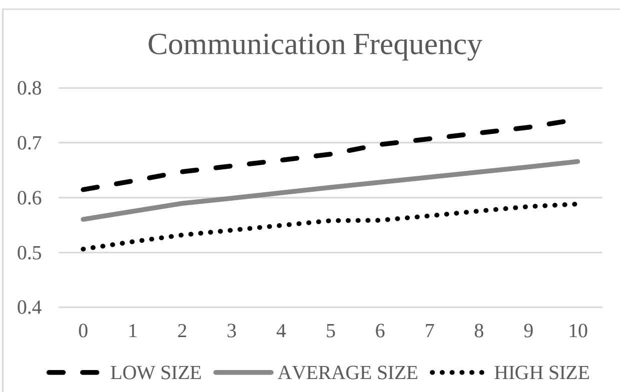
Predicted Growth Curves for the Five Developmental Network Characteristics (Model 2) for Low (- 1 S.D.), Average and High (+ 1 S.D.) Levels of Developmental Network Size; All Other Variables Set at Sample Average






Density
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0 1 2 3 4 5 6 7 8 9 10
LOW SIZE
AVERAGE SIZE
HIGH SIZE


Closeness
3.7
3.6
3.5
3.4
3.3
3.2
3.1
3.0
0 1 2 3 4 5 6 7 8 9 10
LOW SIZE
AVERAGE SIZE
HIGH SIZE


Communication Frequency
0.8
0.7
0.6
0.5
0.4
0 1 2 3 4 5 6 7 8 9 10
LOW SIZE
AVERAGE SIZE
HIGH SIZE

APPENDIX

Definitions and Formulae for Multilevel Models

We estimated five core multilevel models, Models 1a-1d and 2, for each of our five developmental network characteristic outcome variables, average career support, average psychosocial support, density, closeness, and frequency of communication:

(1a) No change: This model estimates the grand mean level of each developmental network characteristic over time, above and beyond the effects of time-varying network size. There is no time predictor:

$$\hat{N}\text{etwork Characteristic}_{it} = \hat{\beta}_{00} + \hat{\beta}_{11}\text{Developmental Network Size}_{it}$$

Here, $\hat{N}$etwork Characteristic$_{it}$ is the predicted value of the developmental network characteristic for Person$_i$ at Year$_t$. $\hat{\beta}_{00}$ is the estimated intercept and $\hat{\beta}_{11}$ is the estimated coefficient for Person$_i$ at Year$_t$ for the time-varying predictor variable, developmental network size.

(1b) Linear change: This model estimates the linear trajectory for each developmental network characteristic over time. It extends model 1a by including linear time (the variable "YEARS") as a predictor.

$$\hat{N}\text{etwork Characteristic}_{it} = \hat{\beta}_{00} + \hat{\beta}_{11}\text{Developmental Network Size}_{it} + \hat{\beta}_{10}\text{YEARS}_{it}$$

Here, $\hat{\beta}_{00}$ is the estimated intercept (the estimated value of the outcome when the predictor YEARS$_{it}$= 0, namely, as the participants were embarking upon their post-business school careers), $\hat{\beta}_{11}$ remains the same as in Model 1a, and $\hat{\beta}_{10}$ is the slope coefficient that quantifies the estimated amount of linear change in the outcome per year.

(1c) Quadratic change: This model investigates whether the developmental network characteristics followed curvilinear, rather than linear, trajectories over time. To do so, we expanded Model 1b by adding a quadratic time predictor (i.e., $YEARS^2$).

$$\hat{N}\text{etwork Characteristic}_{it} = \hat{\beta}_{00} + \hat{\beta}_{11}\text{Developmental Network Size}_{it} + \hat{\beta}_{10}\text{YEARS}_{it} + \hat{\beta}_{20}\text{YEARS}_{it}^{2}$$

Here, the new $\hat{\beta}_{20}$ is the slope coefficient that quantifies the estimated amount of quadratic change in the outcome per year; all other items remain the same as in previous models.

(1d) Cubic change: This model investigates whether the developmental network characteristics followed cubic, rather than linear or quadratic, trajectories over time. We extended Model 1c by adding a cubic time predictor (i.e., $YEARS^3$).

$$\hat{N}\text{etwork Characteristic}_{it} = \hat{\beta}_{00} + \hat{\beta}_{11}\text{Developmental Network Size}_{it} + \hat{\beta}_{10}\text{YEARS}_{it} + \hat{\beta}_{20}\text{YEARS}_{it}^{2} + \hat{\beta}_{30}\text{YEARS}_{it}^{3}$$

Here, the new $\hat{\beta}_{30}$ is the slope coefficient that quantifies the estimated amount of cubic change in the outcome per year; all other items remain the same as in previous models.

(2) Full model: This model includes the parameters from the best fitting model (of 1a-1d) plus all individual- and organizational/industry-level variables as predictors of developmental network characteristics' intercepts. It further includes the interaction of time-varying network size and

time (either linear or linear and quadratic, as determined by the best fitting model from 1a-1d).

The fitted full model for developmental network characteristics whose best fitting model was linear (Model 1b) was as follows:

$$\hat{N}\text{etwork Characteristic}_{it} = \hat{\beta}_{00} + \hat{\beta}_{01}\text{Gender} + \hat{\beta}_{02}\text{Ethnicity} + \hat{\beta}_{12}\text{Marital Status}_{it} + \hat{\beta}_{03}\text{Citizenship} + \hat{\beta}_{04}\text{Years of Work Experience} + \hat{\beta}_{05}\text{Industry prior to MBA program: Financial services} + \hat{\beta}_{06}\text{Industry prior to MBA program: Consulting} + \hat{\beta}_{07}\text{Industry prior to MBA program: Technology} + \hat{\beta}_{11}\text{Developmental Network Size}_{it} + \hat{\beta}_{11}\text{Developmental Network Size}_{it} * \text{YEARS}_{it} + \hat{\beta}_{10}\text{YEARS}_{it}$$

The fitted full model for developmental network characteristics whose best fitting model was quadratic (Model 1c) was as follows:

$$\hat{N}\text{etwork Characteristic}_{it} = \hat{\beta}_{00} + \hat{\beta}_{01}\text{Gender} + \hat{\beta}_{02}\text{Ethnicity} + \hat{\beta}_{12}\text{Marital Status}_{it} + \hat{\beta}_{03}\text{Citizenship} + \hat{\beta}_{04}\text{Years of Work Experience} + \hat{\beta}_{05}\text{Industry prior to MBA program: Financial services} + \hat{\beta}_{06}\text{Industry prior to MBA program: Consulting} + \hat{\beta}_{07}\text{Industry prior to MBA program: Technology} + \hat{\beta}_{11}\text{Developmental Network Size}_{it} + \hat{\beta}_{11}\text{Developmental Network Size}_{it} * \text{YEARS}_{it} + \hat{\beta}_{11}\text{Developmental Network Size}_{it} * \text{YEARS}_{it}^{2} + \hat{\beta}_{10}\text{YEARS}_{it} + \hat{\beta}_{20}\text{YEARS}_{it}^{2}$$

In all above full models, the new $\hat{\beta}_{01}$ through $\hat{\beta}_{07}$ represent the estimated coefficients for the predictor variables and $\hat{\beta}_{12}$ is the estimated coefficient for Person_i at Year_t for the time-varying predictor variable, marital status. All other items remain the same as in previous models.

About the Authors

Shoshana Dobrow Riza is an Assistant Professor of Management at the London School of Economics. Her research has examined the meaning of work, the sense of calling, and developmental mentoring networks in the context of careers, often utilizing longitudinal approaches (s.riza@lse.ac.uk).

Monica Higgins is the Kathleen McCartney Professor of Education Leadership at the Harvard Graduate School of Education. Her research has examined developmental networks and leadership development and, more recently, social entrepreneurship in education (monica_higgins@gse.harvard.edu).